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Reactive power control of isolated wind-diesel hybrid power system using grey wolf optimization technique

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Abstract

In this paper reactive-power control of an isolated wind–diesel hybrid power system is presented. The system generates electrical power from wind by an induction generator (IG) and a synchronous generator (SG) is present for a diesel-generator (DG) set. The mathematical model of the reactive-power balance is presented. In an isolated system IG consumes reactive power which is supplied by the static var compensator (SVC). It also provides reactive power support for load variations. In the type III SVC used here, the proportional integral (PI) controller gains are optimized using Grey Wolf Optimization (GWO) algorithm. Three objective functions namely Integral Time Absolute Error (ITAE), Integral Square Error (ISE) and Integral Time Square Error (ITSE) are considered and their performance is compared in a hybrid system and with earlier work.

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Keywords: Static var compensator (SVC);isolated wind–diesel hybrid power system; Grey Wolf Optimization (GWO); PI controller; ITSE; PSO

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1. Introduction

To maintain generation- load balance and limited life of conventional sources with high pollution rate, research on alternative sources of energy are focused. The renewable sources such as wind, solar, mini/micro hydro, etc. are in geographically dispersed locations close to loads. Such system is termed as distributed or dispersed power system[1]. If it delivers to a local load it is an isolated hybrid power systems[2]. Examples of such are the wind–diesel, wind–diesel–micro hydro systems, wind-diesel- Photo Voltaic system etc. Generators with wind turbine are generally asynchronous or induction generator for variable speed operation. The advantages of such generator over synchronous generator are: reduced unit cost, ruggedness, absence of separate dc source, ease of maintenance, self-protection against severe overloads and short circuits[3]. But the disadvantage of an Induction Generator (IG) lies in its requirement of reactive power to maintain flux. Reactive power can be met by capacitor banks/Synchronous Generator (SG)[4] in an isolated system. Majority of the loads are also inductive. The unequal generation and demand of the reactive power can cause a large voltage variation at generator terminals. Thus, the reactive-power-control strategy of the autonomous wind-diesel hybrid power system needs great improvement to maintain the voltage within the specified limits[5].

Static var compensator (SVC)[6-9] is commonly used for reactive-power control in the transmission system[11]. It is one of the flexible ac transmission systems (FACTS) devices. Though it is primarily concerned with transmission system, it can be used as a source of reactive power in isolated system to improve undesirable voltage fluctuation.

Optimal controller design using swarm optimizations have performed satisfactorily in many areas. Recently, a swarm based optimization- Grey Wolf Optimizer (GWO) has been proposed[12]. This optimization mimics the social behavior of a pack of wolves. Mirjalili et al. have shown superiority of this technique compared to its contemporaries such as Particle Swarm Optimization (PSO), Differential Evolution (DE) and Gravitational Search Algorithm (GSA) in solving the benchmark problems and some of the engineering applications. The SVC used here is type III which consists of a PI controller which signals the firing of SVC. The gains of this controller, Proportional gain K_p and Integral gain K_i are optimized using Grey Wolf Optimization technique.

The paper is organized as follows, Section 2 describes of the modeling equations concisely and Section 3 includes the algorithm of the optimization techniques. Section 4 shows the dynamic responses of the hybrid power systems with the optimal gain obtained followed by the concluding remarks.

2. Modeling Equations

The system taken in this work consists of a diesel generator (DG) set, IG, SVC and consumer loads as shown in Fig.1. The synchronous generator (SG) in DG acts as a reference grid for the IG connected on the wind energy-conversion system. The excitation system in the SG connected on the DG set is IEEE type-I excitation system. The SVC supplies the reactive power deficit apart from the reactive power generated by the SG[8]. The SVC used here is type III as shown in Fig.2.

Frequency is affected by deviation in the real power where as the voltage by reactive power. Here, the prime-mover time constant is greater than excitation time constant, so cross coupling between the load frequency control (LFC) and the automatic-voltage-regulator (AVR) loop is negligible. Thus under steady-state, the reactive-power balance is given by:

$$Q_{SG} + Q_{SVC} = Q_L + Q_{IG} \tag{1}$$

where Q_{SG} = Generated reactive power by SG (pu KVAR); Q_{SVC} = generated reactive power by SVC (pu KVAR); Q_L = load reactive power demand (pu KVAR) and Q_{IG} = reactive power consumed by IG (pu KVAR).

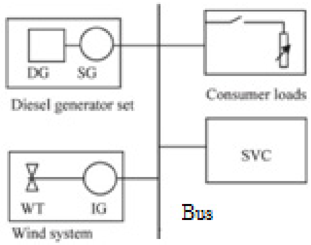


Fig. 1Schematic diagram of general isolated wind–diesel hybrid power system

Let the load reactive power increment by ΔQ_L. The reactive-power generation increases by an amount $\Delta Q_{SG} + \Delta Q_{SVC}$ by the AVR and SVC controller to balance it. The excess reactive-power in the system, becomes $\Delta Q_{SG} + \Delta Q_{SVC} - \Delta Q_L - \Delta Q_{IG}$ and it has twofold effect on the terminal voltage[8] :

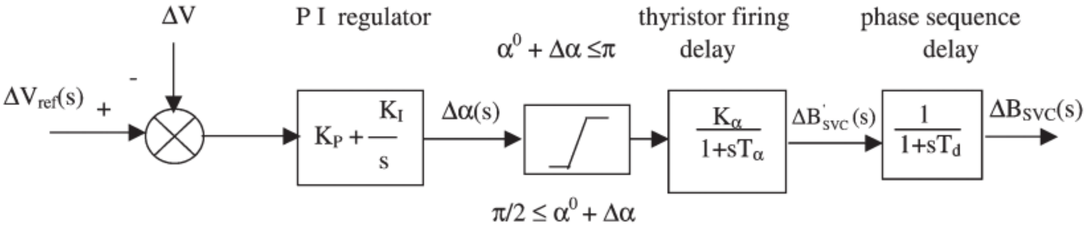


Fig. 2 Linearized models of thyristor-controlled SVC schemes type III[8]

1) Increase the electromagnetic-energy absorption E_M of the IG at the rate $\partial/\partial t(E_M)$;
2) Increase in reactive load demand as a result of increase in voltage ΔV. Mathematically,

$$\Delta Q_{SG} + \Delta Q_{SVC} - \Delta Q_L - \Delta Q_{IG} = \partial/\partial t\,(\Delta E_M) + DV.\Delta V \tag{1}$$

where, ΔE_M, the small change in electromagnetic energy is

$$\Delta E_M = E_M - E_M^0 = 2(E_M^0/V^0)\Delta V \tag{2}$$

wherein V^0 and E_M^0 are the rated values of terminal voltage and electromagnetic energy stored in the IG. All the connected reactive-power-loads experience an increase by $DV = \partial Q_L/\partial V$ (per unit kilovolt-amperes reactive/per unit kilovolt), as a result of increase in voltage. The reactive-power loads can be expressed in the exponential voltage form as [9]:

$$Q_L = C_1 V^q \tag{3}$$

where C_1 is a constant and the exponent q decides type of load. For small perturbations, (3) can be written as

$$\Delta Q_L/\Delta V = q(Q_L^0/V^0) \tag{4}$$

where Q_L^0 is the rated value of the reactive power of load. Taking Q_R as the system reactive-power rating, (1) is rewritten as

$$\Delta Q_{SG} + \Delta Q_{SVC} - \Delta Q_L - \Delta Q_{IG} = 2E_M^0/(V^0 Q_R)\,\partial/\partial t(\Delta V) + DV.\Delta V \tag{5}$$

In (5), Q_R divides only the first term in right hand side as all others are already in pu KVAR. The term E_M^0/Q_R can be written as

$$E_M^0/Q_R = 1/4\Pi f k_R = H_R \quad (6)$$

where H_R is the constant of the system (s) and k_R is the ratio of the system reactive-power rating to rated magnetizing reactive power of IG. Substituting the value of E_M^0/Q_R from (6) in (5), we get

$$\Delta Q_{SG} + \Delta Q_{SVC} - \Delta Q_L - \Delta Q_{IG} = (2H_R/V^0)\,\partial/\partial t(\Delta V) + DV.\Delta V \quad (7)$$

Taking Laplace transform and rewriting

$$\Delta V(s) = K_v/(1 + sT_v)\,[\Delta Q_{SG}(s) + \Delta Q_{SVC}(s) - \Delta Q_L(s) - \Delta Q_{IG}(s)] \quad (8)$$

where $T_v = 2\,H_R/DV\,V^0$ and $K_v = 1/DV$
Now

$$Q_{SVC} = V^2 B_{SVC} \quad (9)$$

where, B_{SVC} is susceptance of SVC.
For small change, the Laplace-transform of above gives

$$\Delta Q_{SVC}(s) = K_6 \Delta V(s) + K_7 \Delta B_{SVC}(s) \quad (10)$$

where $K_6 = 2VB_{SVC}$ and $K_7 = V^2$
Reactive power consumed by IG in Laplace transform, Q_{IG} in terms of generator terminal voltage and generator parameters can be written as[6]

$$\Delta Q_{IG}(s) = K_5 \Delta V(s) \quad (11)$$

where, K_5 is a constant.

The cylindrical rotor synchronous machine model for small perturbation In Laplace transform is given by two equations

$$\Delta Q_{SG}(s) = K_3 \Delta E_q'(s) + K_4 \Delta V(s) \quad (12)$$

where, $K_3 = V cos\delta/X_d'$ and $K_4 = (E_q' cos\delta - 2V)/X_d'$ and

$$(1 + sT_G)\Delta E_q'(s) = K_1 \Delta E_{fd}(s) + K_3 \Delta V(s) \quad (13)$$

wherein, $T_G = (X_d' T_{d0}')/\,X_d$, $K_1 = X_d/X_d'$ and $K_2 = [(X_d - X_d')\,cos\delta]/\,X_d$

where, δ is the power angle;X_d and X_d' are direct axis synchronous reactance under steady state and transient condition respectively. The transfer function of the system with the fixed coefficients same as[8] are taken to develop the model shown in Fig.3.

3. Grey Wolf Optimizer (GWO)

It is a new meta-heuristic that mimics leadership order and preying behaviour of grey wolves in a group (Canis lupus)[12]. Grey wolves are hierarchically categorised into alpha, beta, delta, and omega in the pack[12]. The pack works for hunting, searching for prey, encircling prey and attacking prey. The leaders are a male and female, called alphas. The leader alpha decides the packs action. The entire pack acknowledges the alpha by holding their tails down. Only the alphas mate in the pack. The alpha dominates as a good administrator. It may not be the strongest member of the pack.

The second level consists of beta. They are subordinate wolves that help the alpha in decision-making or other pack activities. The beta wolf can be either male or female, and is the next best successor in case one of the alpha wolves ceases. It plays the role of an advisor to the alpha and discipliner for the pack. Omegas are in the third level from top. They have to submit to all the other dominant wolves. They are the last wolves that are allowed to eat.

Though omega are least ranked, the whole pack faces internal fighting and problems without them. They help to satisfy the whole pack and maintaining the dominance structure. If a wolf is not an alpha, beta, or omega, he/she is called subordinate (or delta in some references). Delta wolves have to submit to alphas and betas, but they dominate the omega.

Social behaviour of grey wolves are-

- Tracking, chasing, and approaching the prey
- Pursuing, encircling, and harassing the prey until it stops moving
- Attack towards the prey

Thus the steps of the algorithm are modeled mathematically as follows.

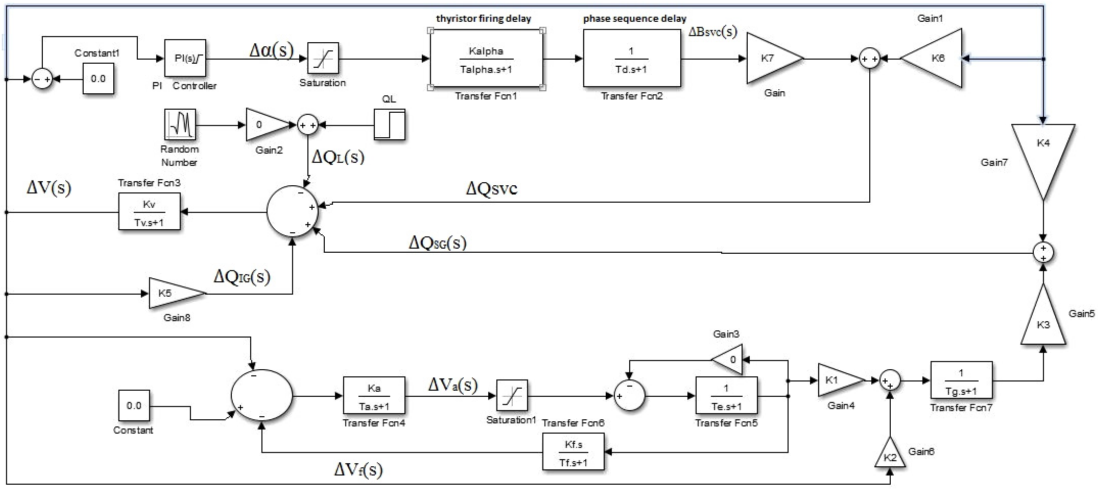


Fig. 3 Diagram of transfer-function model for the reactive-power control of the wind–diesel hybrid power system

3.1. Encircling prey

Grey wolves encircle prey during the hunt maintaining a radial distance. The distance of a wolf from a prey is given by D

$$\vec{D} = |\vec{C}\vec{X}_p(t) - \vec{X}(t)| \tag{14}$$

$$\vec{X}_1(t+1) = \vec{X}_p(t) - \vec{A}\vec{D} \tag{15}$$

where t indicates the current iteration, $\vec{A}$ and $\vec{B}$ are coefficient vectors, $\vec{X}_p$ is the position of the prey and $\vec{X}$ indicates the position vector of a grey wolf.

The vectors and are calculated as follows:

$$\vec{A} = 2.\vec{a}.\vec{r}_1 - \vec{a} \tag{16}$$

$$\vec{C} = 2.\vec{r}_2 \tag{17}$$

where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations to approach the solution or prey and $\vec{r}_1, \vec{r}_2$ are random vectors in [0,1]. Thus, the parameter $\vec{C}$ is randomly set in each iteration.

3.2. Hunting

It is a group effort. Grey wolves can identify the location of prey and encircle them. The hunting is guided by the alpha. Occasionally the beta and delta also participate in hunting. It is assumed that the alpha has best candidate solution and next two: beta and delta have better knowledge about the potential location of prey or the solution. Three best solutions obtained in an iteration are used to update the position of all. The updation is as follows:

$$\vec{D}_\alpha = |\vec{C}_1\vec{X}_\alpha - \vec{X}|, \vec{D}_\beta = |\vec{C}_2\vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C}_3\vec{X}_\delta - \vec{X}|$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1\vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2\vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3\vec{D}_\delta$$

$$\vec{X}(t+1) = \frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3} \tag{18}$$

Where $\vec{D}$ with subscript α, β and δ are the distances and the position of alpha $\vec{X}_1$, beta $\vec{X}_2$ and delta $\vec{X}_3$ are updated according to respective$\vec{D}$s.

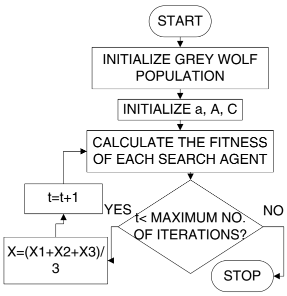


Fig. 4 Flow chart of Grey Wolf Optimization (GWO)

3.3. Search for prey (exploration)

For A ϵ [-1, 1] grey wolves reduce distance from prey exploiting social information. Beyond this boundary, they diverge from each other to explore better prey. Thus GWO algorithm explores globally. C provides random weights for prey to give importance (C>1) or neglect (C<1) in defining the distance. This assists GWO to perform random search, favoring exploration and jump from local minima. The randomness in C vector can be seen as the effect of obstacles to reach the prey.

The search process starts with creating a population of grey wolves put randomly in the search space as in flow chart (Fig.4) of GWO. Over the course of iterations, alpha, beta and delta wolves indicate more likely solutions. Each solution updates its distance from the prey. By hunting probable solutions are obtained. The adaptive values of parameters a and A allow GWO to smoothly transition between exploration and exploitation. It is simple, with only two parameters a and C to be adjusted. The algorithm terminates finally when the end criterion is satisfied.

3.4. Objective function

GWO is used to minimize three of the standard objective functions[10]:

ITAE (Integral Time Absolute Error)- $J_1 = \int_0^{Tsim} T|\Delta V|\, dT$

ISE (Integral Square Error)-$J_2 = \int_0^{Tsim} \Delta V^2 \, dT$

ITSE (Integral Time Square Error)- $J_3 = \int_0^{Tsim} T(\Delta V)^2 \, dT$

Here ΔV, deviation in terminal voltage is the parameter, which is to be minimized under load by reactive power support from different sources. The simulation time T_{sim}=0.1s as the transient should die out within 4 cycles.

4. Results and response of optimal controller

In this section, the simulation results are presented. The model described in the previous section was simulated in MATLAB® Version 2011a on DELL PC Intel® Core™ i5-2430M, 2.40 GHz and 4 GB RAM and the output transient responses are outlined and compared to find the optimized K_p and K_i. The system parameters are taken as in[8] .

The model was simulated without a controller and the graph for ΔV was plotted as in Fig.5.

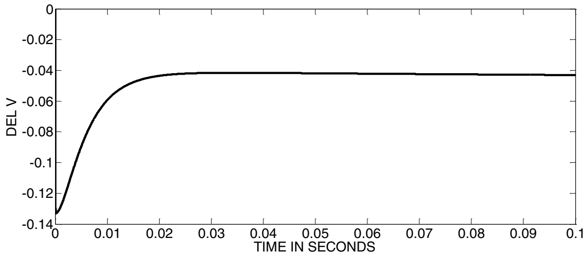


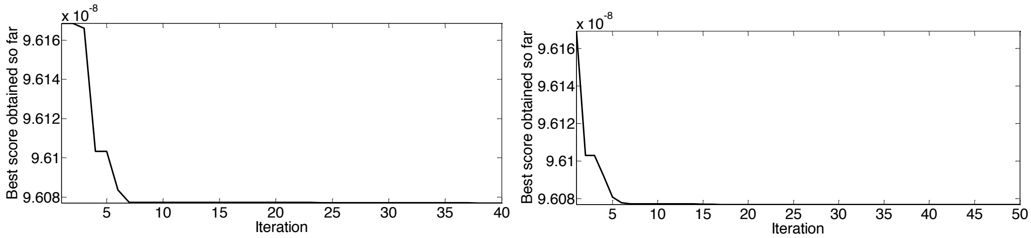
Fig. 5 Variation of deviation in voltage with time without controller

The model was simulated and the following K_p, K_i and the objective function's minimum value was noted down. For a given objective function, the number of agents and iterations were increased. The convergence was noted down for 50 runs. The best values are tabulated in table 1. The set of the values for K_p and K_i which give the minimum value of the objective function were selected and further compared with other error criterions. The result of ITSE as objective function minimized with GWO and particle swarm optimization (PSO) for similar no. of agents and iterations shows GWO minimizes more effectively.

The values of K_p and K_i selected for different error criterions are used in simulated model and the transient response parameters are recorded in table 2. It is observed that ΔV settles to -0.04 and never settles to zero for a

Table 1. Effect of parameter variation of GWO

OBJECTIVE FUNCTION	SEARCH AGENTS	MAX. ITERATIONS	K_p	K_i	OBJECTIVE FUNCTION VALUE
ITAE	30	40	2738.0048	4250.3266	$1.5500 X10^{-6}$
	30	50	**1118.1940**	**4274.2174**	**$1.5468\ X10^{-6}$**
ISE	30	40	18857.5660	14.2543	$5.001962\ X10^{-5}$
	30	50	**18137.9764**	**194.8630**	**$5.001870\ X10^{-5}$**
ITSE	30	40	1668.1496	4185.2400	$9.607745\ X10^{-8}$
	30	50	**1771.2759**	**4183.1733**	**$9.607721\ X10^{-8}$**
ITSE & PSO	30	50	**4261.2345**	**4993.8140**	**$9.613193\ X10^{-8}$**



(a) Search agents=30, iteration=40 (b) Search agents=30, iteration=50

Fig. 6 Convergence plots for ITSE

step increase in the reactive load. The values of K_p and K_i were optimized using the GWO optimization technique for the PI controller in SVC.

It is observed from Fig.6 that the objective function converges properly with the search agents =30 and maximum iterations=50 for GWO. The transient responses for the optimal controller obtained are given below in Fig.7(a).

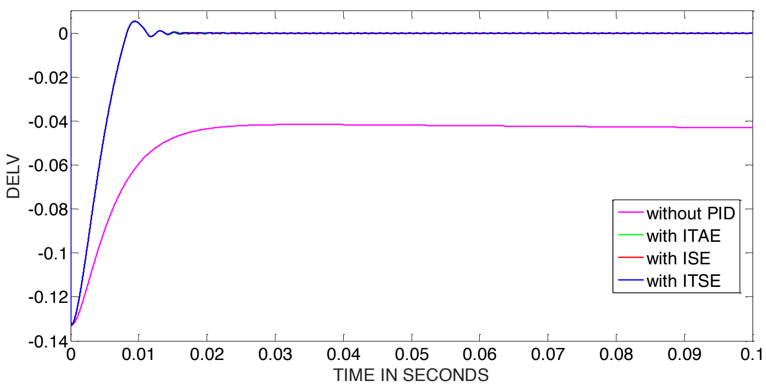
Although the settling time for the three errors remain same, the stability can be analysed from the first undershoot. A close look of the magnified plots of ΔV vs. time (Fig.7(b)) suggests that the choosing ITSE as the objective function has the minimum undershoot.

It is observed that even though the overshoot in ΔV for ISE is less than the ITSE, variation of voltage with time for ISE is oscillatory in nature. It is seen for ITAE that the ΔV is less oscillatory in nature, at the same time the undershoot in ΔV is more, so ITSE is found best for this problem as compared to earlier work[8].

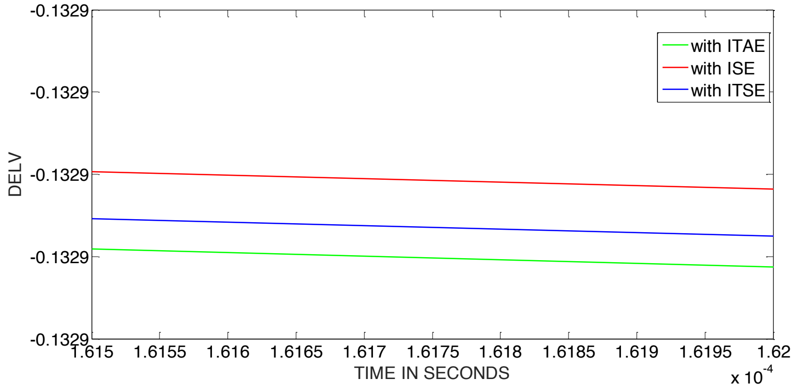
Therefore, the K_p and K_i values corresponding to the ITSE from table 2 are taken for further calculation of performance indices. The model is simulated using the best values of K_p and K_i. The transient responses obtained for different measured parameters are shown in Fig.8. The oscillations in ΔV, ΔE_q', ΔE_{fd}, ΔE_q firing angle, ΔQ_{SG} and ΔQ_{IG} settle with contribution of Q_{SVC}.

Table 2 Comparison of controller design for transient response of variation of terminal voltage

K_p	K_i	Settling Time (s)	Overshoot (%)	Undershoot (%)
1118.1940	4247.2174	0.0106	+0.0054	-0.1329
18137.9674	194.8630	0.0106	+0.0054	-0.1329
1771.2759	4183.1733	0.0106	+0.0053	-0.1329
1	0	0.0179	-0.0416	-0.1331

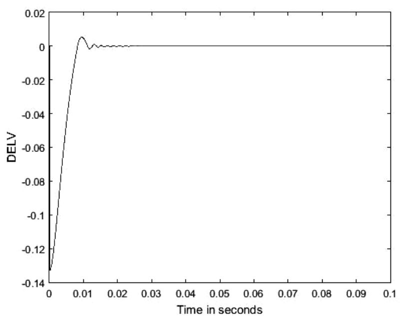


(a)

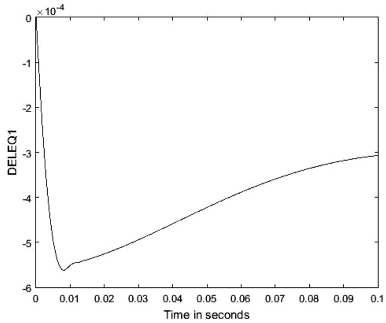


(b)

Fig. 7 Variation of terminal voltage (ΔV) with time for different objective functions (a) For 0.1 s; (b) Magnified view



(a)



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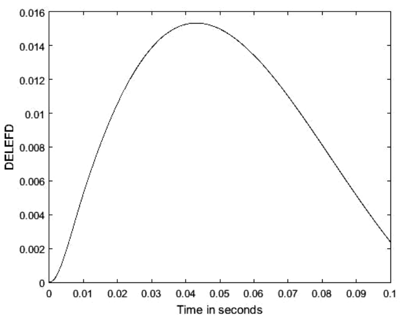

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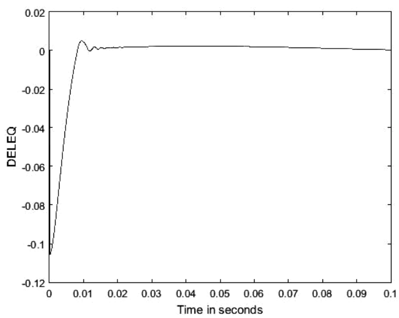

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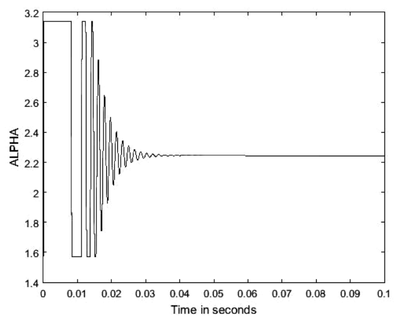
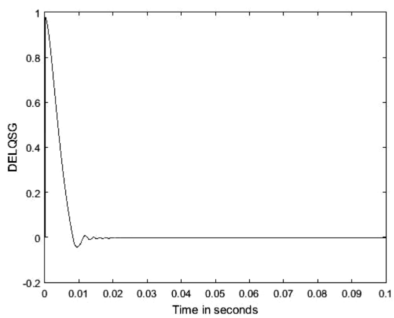
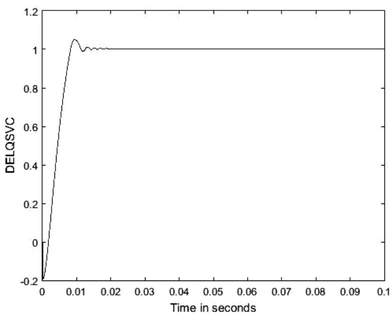


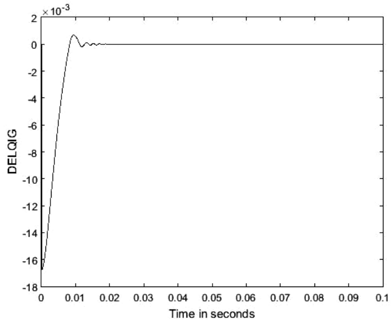
(e)



(f)



(g)



(h)

Fig. 8(a)-(h)Transient responses for hybrid power system with 1% increase in power load

Without use of the SVC control, the steady state error does not die out even after the oscillations settle. But, there is minimal steady-state error in the terminal voltage of the system (Fig.8(a)) with SVC control; therefore, the deviation in the reactive power required by the IG vanishes. It is observed that, the SVC meets the increase in the reactive-power demand by load. In all of the three error criteria, it is found that the oscillation vanishes in about 0.0106 s.

5. Conclusion

A dynamic voltage stability study has been presented in this paper for the isolated wind–diesel hybrid power system considering a transfer-function model based on a small signal analysis. The reactive-power-flow equations have been detailed for hybrid systems for automatic reactive-power-control model. It is observed that increase in the search agents and number of iterations of GWO results in a better convergence. It also supersedes PSO. In the similar fashion three sets of values of controller K_p and K_i are found out and finally the ITSE criterion was selected due to low undershoot with designed controller. The parameters of the controllers can be improved or advanced control methods and optimization techniques can be used in future to improve the stability and dynamic performance of isolated wind-diesel hybrid power systems. Various combinations of hybrid generation systems like solar energy and micro hydel plants can also be hybridized and can be worked upon.

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